Automated system to measure Tandem Gait to assess executive functions in children

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ABSTRACT

As mobile technologies have become ubiquitous in recent years, computer-based cognitive tests have become more popular and efficient. In this work, we focus on assessing motor function in children by analyzing their gait movements. Although there has been a lot of research on designing automated assessment systems for gait analysis, most of these efforts use obtrusive wearable sensors for measuring body movements. We have devised a computer vision-based assessment system that only requires a camera which makes it easier to employ in school or home environments. A dataset has been created with 27 children performing the test. Furthermore, in order to improve the accuracy of the system, a deep learning based model was pre-trained on NTU-RGB+D 120 dataset and then it was fine-tuned on our gait dataset. The results highlight the efficacy of proposed work for automating the assessment of children's performances by achieving 76.61% classification accuracy.

CCS CONCEPTS

• Computing methodologies → Activity recognition and understanding.

KEYWORDS

tandem gait, cognitive assessment, computer vision, deep learning

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1 INTRODUCTION

Executive functions are high-order mental processes that enable us to successfully plan, multitask, focus, remember instructions,

switch tasks and coordinate. forming the foundation of the cognitive development. They mostly rely on brain functions such as working memory, mental flexibility, motor skills, and others. Motor skill is one of the important skills that humans learn during their childhood. They generally involve movements of the large muscles in the arms, legs, and torso. Humans rely on these skills for their every day activities at home, work/school, and in the community. Children affected with neurological conditions such as ADHD exhibit motor abnormalities [2, 11], especially when it comes to balance. Such impairments when not treated at the right time can affect everyday activities of a person that in turn can affect other functions such as fine motor skills. Building an automated system to access such disorders paves way for an efficient diagnosis and treatment.

The NIH toolbox is a standardized set of tests for cognitive assessment that empowers automated assessment through sensors and mobile applications. Specifically, there are numerous tests to assess balance which require sensors such as accelerometer that is attached to the body to measure it. The overall goal of this work is to build a low-cost automated assessment system that uses computer vision to analyse participants performing the task and score them on the basis of standard cognitive measures such as gait and balance.

In this work (Figure 1), the focus of the automated assessment system is on the "Tandem gait" task which is part of a larger system called ATEC-Activated Test of Embodied Cognition [1, 3, 17]. A dataset has been created with 27 children performing the gait task. In order to automatically evaluate subject's performance, first VIBE [9] human pose estimation system was used to extract 3D body key-points. Then a deep learning based model was trained to classify subject's steps as valid or invalid. Furthermore in order to improve the accuracy of the system, the model was pre-trained on NTU-RGB+D 120 dataset and then fine-tuned on our gait dataset. Contrastive learning [5] framework was employed to pre-train the model in self-supervised manner. The results shows that pre-trained model can achieve satisfying results even when small amount of annotated data is available for training.

The rest of the paper is structured as follows: Section 2 discusses the related work, Section 3 explains the setup for data collection with information about the gait dataset. Section 4 describes the proposed method along with the results. Finally, conclusion and future works are mentioned in section 5.

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Figure 1: Proposed method architecture. Top (pink): Supervised classification. Bottom (blue): self-supervised pre-training.

Figure 2: Data collection setup.

2 RELATED WORKS

There has been a plethora of research in recent years that tackle the problem of analysing body gait for prediction and diagnosis of multiple disorders. In [13], machine learning methods have been widely used for gait assessment through the estimation of spatio-temporal parameters. The proposed methodology was tested on gait data recorded on two pathological populations (Huntington's disease and post-stroke subjects) and healthy elderly controls. They used data from inertial measurement units placed at shank and waist. In [14], wearable sensor technologies were employed for development of new methods for monitoring parameters that characterize mobility impairment such as gait speed outside the clinic. In their work, authors try to extend these methods that are often validated using normal gait patterns to subjects with gait impairments.

The focus of the work described in [7] was on diagnosis of Vascular Dementia during or prior to vascular cognitive impairment. They explored gait analysis which include stride length, lateral balance, or effort exerted for a particular class of activity. Although gait has clear links to motor activities, they investigate an interesting

link to visual processing since the visual system is strongly correlated with balance. Various gait metrics have been investigated, and their potential to identify vascular cognitive impairment has been evaluated. In [19], the issue of support for diabetic neuropathy (DN) recognition is addressed. In this research, gait biomarkers of subjects is used to identify people suffering from DN. To achieve this, a home-made body sensor network was employed to capture raw data of the walking pattern of individuals with and without DN. The information was then processed using three sampling criteria and 23 assembled classifiers in combination with a deep learning algorithm.

Figure 3: Example of tandem gait task; (a) Skeleton key points, (b) An invalid step, (c) A valid step.

In [6], the effects of human fatigue due to repetitive and physically challenging jobs that cause Work-related Musculoskeletal Disorder (WMSD) was investigated. This study was designed to monitor fatigue through the development of a methodology that

Table 1: Different methods top-1 classification accuracy for different train/test split. 80%: Using 80% of dataset for training and remaining 20% for testing. 50%: Using 50% of dataset for training and remaining 50% for testing. 10%: Using 10% of dataset for training and remaining 90% for testing.

Method	80%	50%	10%
Supervised	72.39	63.33	52.13
Contrastive Learning (E2E)	76.61	72.44	70.90
Contrastive Learning (MoCo)	76.61	74.03	72.46

objectively classifies an individual's level of fatigue in the workplace by utilizing the motion sensors embedded in smartphones. Using Borg's Ratings of Perceived Exertion (RPE) to label gait data, a machine learning algorithms was developed to classify each individual's gait into different levels of fatigue. Finally, in [15], the aim of the study was to determine whether gait and balance variables obtained with wearable sensors could be utilized to differentiate between Parkinson's disease and essential tremor.

3 DESCRIPTION OF THE DATASET COLLECTED

In this section, the data collection setup along with the characteristics of dataset are explained. Figure 2 represents our video-based data collection setup. An RGB camera was used to collect the side view of the child performing the task. The recording modules were connected to an android-based interface which was controlled by the administrator (parents, teachers) to monitor the flow of the assessment.

Data was collected from children between the ages of 6 and 10 across multiple school in the United States. Participants were invited to perform the assessment task in a classroom environment after parents consenting and completing the screening procedure required by the study protocol. A total of 27 recordings from 27 children were collected. In each recording, the kid was asked to perform 8 valid steps. A step is considered valid only if the heel of one foot touches the toe of another foot. Then subject's 3D body key-points were extracted using VIBE system [9]. VIBE (Video Inference for Body Pose and Shape Estimation) is a video pose and shape estimation method that predicts the parameters of SMPL body model for each frame of an input video. From these key-points 17 of them including head, hands, hip, feet and toes were selected. Finally, the extracted data were divided into 8 equal segments (with overlap), each corresponding to an step. An example of a valid and an invalid step are presented in Figure 3. In these figures, children's body are covered by their estimated SMPL body mesh in order to see VIBE system body pose estimation in action and also to protect their privacy.

In order to evaluate the performance of our system, each task performed by a child was manually scored by our assistants. These scores later acted as the ground truth for our algorithm. In order to pre-train the classifier model, publicly available NTU-RGB+D 120 [12, 18] were used. This dataset contains 120 action classes and 114,480 video samples. In this work only 3D skeletal data were

employed. Similar to gait dataset, 17 equivalent key-points (head, hands, hip, feet and toes) were selected.

Figure 4: Different contrastive learning architecture (q stand for query and k for key) . Left: End-to-End training of encoders (E2E). Right: Using a momentum encoder as a dynamic dictionary lookup (MoCo). [5]

4 PROPOSED METHOD AND RESULTS

After 3D body joints were extracted from input videos, they were divided into 8 segments with equal size. Each segment ($X \in \mathbb{R}^{32 \times 51}$) includes 32 samples with 51 features. The feature are x,y,z coordinates for each 17 key-points rasterized into one vector. Then, input was fed into an encoder network to obtain the compact representation $z \in \mathbb{R}^{256}$. Finally a linear classifier is used to classify input segments into valid and invalid segments (Figure 1). In this work, a 4 layer 1D Convolutional Neural Network (CNN) [10] is used as encoder network.

For evaluating the performance of proposed methods in case of small amount of annotated data three scenarios were defined. In first scenario, 80% of data was used for training and remaining 20% for testing. In second scenario, 50% of data was used for training and other 50% for testing. Finally for scenario 3, 10% of data was used for training and remaining 90% for testing. The average classification accuracy was calculated by cross-validation. The results for baseline supervised method is shown in first row of Table 1. It is clear from the results that the baseline method classification accuracy decreases as training set becomes smaller.

In order to improve the performance of the proposed system, we tried to pre-train encoder network on large NTU-RGB+D 120 dataset by using self-supervised training [5, 20]. One of the most popular self-supervised approaches is contrastive learning (CL) [4, 5]. CL tries to group similar samples closer and diverse samples far from each other. To achieve this, a similarity metric (cosine similarity) is used to measure how close two representations are from each other. Representations are obtained by feeding input data into an encoder network. During training, one sample (query x^q) from the training dataset is taken and a transformed version (or another view in NTU dataset) of the sample is considered as a positive sample (positive key x^{k+}), and the rest of the samples are considered as negative samples (positive key x^{k-}). Training encourages encoder network to differentiate positive samples from the negative ones.

Since number of negative samples affect the performance of CL methods [5], different strategies are used for selecting a large number of negative samples. In this work, two of these strategies called E2E and MoCo are used. Their architecture are depicted in Figure 4. In End-to-End learning (E2E) a large batch size is used and all the samples in the batch except for the query and one positive sample are considered as negative.

Because large batch sizes inversely affect the optimization during training, one possible solution would be to maintain a separate dictionary known as memory bank containing representations of negative keys. However, since maintaining a memory bank during training is complicated, the memory bank can be replaced by a Momentum Encoder. The momentum encoder (MoCo) [4] generates a dictionary as a queue of encoded keys with the current mini-batch enqueued and the oldest mini-batch dequeued. The momentum encoder shares the same parameters as the query encoder (θ_q) and its parameters (θ_k) gets updated based on the parameters of the query encoder. ($\theta_k = m\theta_k + (1 - m)\theta_q, m \in [0, 1)$: momentum coefficient)

All of the above methods were trained using Pytorch framework [16] for 100 epochs. Also ADAM [8] was employed as optimizer with learning rate: 1×10^{-4} , β_1 : 0.5 and β_2 : 0.999. Furthermore, for all contrastive learning methods temperature hyper-parameter τ and momentum coefficient μ were chosen as 0.1 and 0.999 respectively. The results show that as the number of annotated data decreases, the performance of supervised method decreases dramatically whereas self-supervised methods maintain their performance.

5 CONCLUSION AND FUTURE WORKS

In this work, we presented a dataset that incorporates recordings from 27 children performing the Tandem Gait task. We also designed a computer vision system with acceptable precision that analyzes a child's performance by counting the number of valid steps performed in the task. Our proposed method performs well even in case of having access to small amount of annotated training data. Applying the proposed approach on all different tasks defined in ATEC such as ball-drop [17, 20], finger-oppose [1], etc., and finally designing a general framework for cognitive assessment of children will be focus of future works.

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